Investigating the association between mating-relevant self-concepts and mate preferences through a data-driven analysis of online personal descriptions.

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Abstract

Research on mate preference have often taken a theory-driven approach; however, such an approach can constrain the range of possible predictions. As a result, the research community may inadvertently neglect traits that are potentially important for human mate choice if current theoretical models simply do not identify them. Here, we address this limitation by using a data-driven approach to investigate mating-relevant self-concepts (i.e., what individuals believe to be attractive about themselves). Using Latent Dirichlet Allocation (LDA; a clustering method developed in computer science) and a large sample of written descriptions from online personal advertisements (N = 7,973), we identify 25 common topics that individuals use when advertising themselves. Men were more likely to advertise education/status, while women were more likely to discuss being honest/nurturing and caring for pets. We also assessed patterns of universal and compatible mate preferences for these 25 topics by collecting ratings of desirability from a separate group of 100 participants on a subset of these profiles (N = 468). Participants were also asked to write a personal description of themselves as if they were writing for a dating website. Overall, both male and female profiles that discussed outdoor activities, and music/art were rated as more desirable, while women that discussed a healthy lifestyle and friends/family were also rated as more desirable. Both men and women who discussed sex or mentioned being a parent were rated as less desirable. When comparing the topic probabilities between profiles collected online and those written by the raters, we found that raters preferred profiles that were more similar to their own, particularly for topics to do with being outgoing and agreeable.

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Human mate preference research provides important insight to human social and sexual relationships. Who we choose as a partner is important for many outcomes, including physical and mental health (Coombs, 1991; Fletcher, Fitness, & Blampied, 1990). Also, research on human mate preferences provides important theoretical insights, as sexual selection is a major driver of human evolution (Kingsolver et al., 2001) and a large component of sexual selection is who we prefer and choose as a partner (Kokko, Brooks, McNamara, & Houston, 2002). Broadly, research on human mate preferences has investigated two types of preferences: 1) universal preferences, which are preferences shared by most humans, or shared by a population of individuals based on sex, other demographics, or context; and 2) individualised preferences, where an individual's preferences are based on their own characteristics.

Research on universal preferences is often based on biological models, which stipulate that there is strong selection pressure on choosing a partner with traits that are likely to maximise one's own fitness (i.e., an individual's genetic contribution in the following generation). Therefore, over multiple generations, humans have been shaped by evolution to share preferences for traits that are evolutionarily advantageous. Classic examples of universal preferences are findings such as men (compared to women) being more likely to prioritise indicators of fertility when evaluating a potential partner, such as youth (Kenrick & Keefe, 1992) and physical attractiveness (Buss, 1989; Li, Bailey, Kenrick, & Linsenmeier, 2002), and women (compared to men) being more likely to prioritise indicators of resource provisioning potential, such as social status (Buss, 1989; Feingold, 1992) or relationship commitment (Buss & Schmitt, 1993).

Research on individualised preferences (also referred to as compatible preferences) have found that individuals are attracted to others who are more similar to themselves (Hitsch, Hortaçsu, & Ariely, 2010). This research is based on theories of assortative mating, which suggests that people are more likely to interact with, connect with, and be attracted to partners who share similar interests or characteristics. Indeed, couples in romantic relationships tend to be more similar across many domains, including social status (Kalmijn, 1994), personality (Botwin, Buss, & Shackelford, 2006), and intelligence (Mascie-Taylor & Vandenberg, 1988; Watson et al., 2004). Partner similarity has also been linked to relationship satisfaction (Gonzaga, Carter, & Buckwalter, 2010; Luo & Klohnen, 2005; but see Watson et al., 2004). However, whether individuals show a preference for matching is debated, with other studies not finding that couples tend to match on personality traits (Lewak, Wakefield Jr., & Briggs, 1985; Robins, Caspi, & Moffitt, 2000), and speed-dating studies that suggest matching only has a weak influence on relationship outcomes (Asendorpf, Penke, & Back, 2011; Belot & Francesconi, 2013). While research on individualised preferences also encompasses preference for dissimilarity (i.e., the adage that opposites attract), evidence for disassortative mating patterns is limited.

Integral to our understanding of human mate preference is what individuals believe to be attractive about themselves (i.e., individual's mating-relevant self-concepts). Individuals are motivated to present themselves favourably to potential partners (Toma & Hancock, 2010). As such, how individuals present themselves or what they choose to reveal are likely contingent on what they believe others find attractive (both in general and specifically about themselves). This, in turn, would influence mating success. There are potentially many factors that could influence an individual's beliefs about what is attractive about themselves; for instance, mating-relevant self-concepts and presentation strategies could have been shaped via evolution, as it would be evolutionarily advantageous to hold beliefs that enhance one's own mating success. Another possibility is that mating-relevant self-concepts could be informed by social factors, such as stereotypes regarding gender roles. Despite its potential importance, little empirical work has investigated the influence of mating-relevant self-concepts on preferences and mating success.

To date, research on mate preferences has predominantly taken a theory-driven approach, where traits thought to be important for mate choice are chosen and investigated based on theory.

While a theory-driven approach has many advantages, it can also constrain the range of possible predictions, and what is predicted can be susceptible to biases held by the research community (i.e., researchers may inadvertently be more incline to make certain predictions and be blind to others based on preconceptions; Jack, Crivelli, & Wheatley, 2018). As a result, traits that are potentially important for human mate choice may be completely neglected if current theoretical models do not identify them. This issue is particularly problematic for research on human mating, as biological models of human mate choice are often based on the mating systems of non-human animals (e.g., lekking species, characterised by intense intrasexual competition, elaborate male ornamentation, and the absence of stable pair-bonds), which can vary greatly from the mating system of modern humans, commonly characterised by mutual mate choice, extended courtship, and formation of stable pair-bonds (Roberts & Havlíček, 2013; Stewart-Williams & Thomas, 2013).

Additionally, theory-driven research tends to focus on explaining the causes of behaviour with increasingly intricate theories that, in reality, have little ability to predict future behaviour (Yarkoni & Westfall, 2017). An example where solely relying on theory-driven research has become problematic is research on facial attractiveness, where the predominant theories from the past few decades have stipulated that facial traits such as symmetry, averageness, and sexual dimorphism are attractive (Fink & Penton-Voak, 2002; Thornhill & Gangestad, 1999). Because of these theories, the majority of research on facial attractiveness conducted over the past decade has fixated on these limited traits, despite the fact that they may be relatively poor predictors of facial attractiveness (Cai et al., 2018; Holzleitner et al., Submitted; Said & Todorov, 2011).

The limitations of theory-driven approaches can be addressed by using a data-driven approach (Jack et al., 2018; Yarkoni & Westfall, 2017). This approach is where relationships are identified from many observations of highly variable data, and therefore is theoretically free and resistant to researcher bias. Given the inherent noisiness of a dataset with high dimensionality, sizes of potential effects are likely to be small, and therefore require a large number of observations to detect. As such, data-driven methods can be resource intensive to collect and analyse. However, advances in computing power and availability of big data have recently allowed data-driven research to become more feasible. Complementing theory-driven research with data-driven approaches has given insight in other research areas that were not evident (or predicted) in studies using theory-driven approaches; for instance, recent data-driven analyses have indicated that facial traits identified by theory (symmetry, averageness, and sexual dimorphism) are relatively poor predictors of facial attractiveness (Holzleitner et al., Submitted; Said & Todorov, 2011), suggesting that previous research has been focusing on relatively unimportant traits. Another example from research on romantic attraction using machine learning techniques have found that while a good proportion of variance can be accounted for by the actor and target, predicting preferences from a combination of their traits (i.e., compatibility) is challenging (Joel, Eastwick, & Finkel, 2017).

Online dating has become a popular method of meeting potential partners, with 22% to 35% of recently married couples in the U.S. stating they had first met online (Cacioppo, Cacioppo, Gonzaga, Ogburn, & VanderWeele, 2013; Rosenfeld & Thomas, 2012). Typically, online dating involves individuals posting personal advertisements of themselves on dedicated websites with the aim of attracting a partner. Given the continual rise of online dating, and that individuals on this platform are free to advertise themselves however they choose, mating-relevant self-concepts are likely to play a large role in mating success in modern romantic and sexual relationships.

Data from online dating is ideal for a data-driven investigation of mating-relevant self-concepts for several reasons. First, given that individuals are free to advertise any aspect of themselves and are motivated to present themselves favourably (Toma & Hancock, 2010), a large sample of online dating profiles is likely to encompass a large spectrum of traits that people consider to be important when advertising themselves to potential mates, thus fulfilling the need for high dimensionality. Also, a large number of online dating profiles are readily available, which is required when using data-driven approaches. In addition, given that these are genuine attempts to attract a partner, findings from analysing online personal advertisement are ecologically valid. While some previous research has investigated traits individuals tend to emphasise in personal advertisements (both online and from newspapers), these studies have only investigated traits chosen by researchers from theoretical models of human mate choice (e.g., Bereczkei, Voros, Gal, & Bernath, 1997; Feingold, 1992; Hitsch et al., 2010; Kenrick & Keefe, 1992; Waynforth & Dunbar, 1995; Wiederman, 1993), and therefore suffer from the limitations of theory-driven research mentioned above.

Here, we used a data-driven approach to investigate mating-relevant self-concepts from online written dating profiles. First, using techniques established in the computer sciences, we identify common topics that individuals use when advertising themselves to potential mates online (Study 1). Second, we assess how these topics relate to universal and individualised patterns of human mate preferences (Study 2).

STUDY 1

In Study 1, we identify common topics that individuals use when advertising themselves online (i.e., their mating-relevant self-concepts). First, we collected a large sample of publically available online dating personal description (i.e., freely available without agreeing to any terms of service or creating a profile). We then analysed this data using Latent Dirichlet Allocation (LDA; Blei, Ng, & Jordan, 2003), a clustering algorithm developed in computer science to identify common themes that appear in a corpus of text. LDA is a method of simultaneously estimating both the words that make up a topic, and the topics contained in each document (Blei et al., 2003; Silge & Robinson, 2017), and is commonly used to analyse web material, such as website documents and Twitter posts (Murphy, 2017; Tirunillai & Tellis, 2014). LDA is also advantageous over other topic modelling techniques as it allows documents to be made up of multiple topics, rather than being categorised into exclusive discrete groups, which is likely a better representation of how text is used online and in personal advertisements. LDA also has the advantage of estimating the probability that each document contains every topic. When applied to online dating profiles, we are able to determine common topics that individuals gravitate towards when attempting to attract a partner online. We can also test for how these topics are used by different profile writers (e.g., between men and women) to give insight into how mating-relevant self-concepts vary according to different contexts.

Method

Dating Profiles

The protocol for collection of online dating profiles and subsequent analysis were approved by the University of Glasgow ethical review process. Written descriptions, main profile image, and some demographic details (e.g., age, sex, location) were autonomously collected using the RSelenium package in R (Harrison & Kim, 2017) between January 2017 and April 2017 from publically available dating advertisements posted online. Here, our analyses focused solely on the written descriptions. Profiles were randomly sampled from available, accessible profiles with the only criterion being that individuals were between the ages of 18-60, resulting in a sample of 10,024 profiles. The majority of profiles were located in the United States (N = 6318, 63.03% of the full sample), but ranged in locations worldwide (see Pages 4-6 of the supplementary materials for the full breakdown). Of these, 196 profiles were duplicates and were removed from the sample. A further 1,525 descriptions contained no text, and another 45 descriptions included just punctuation or symbols (e.g., a single full stop), and were also removed from the sample. Written descriptions that were not in English (*N* = 351) were translated using Google Translate (http://translate.google.com) and translations that were not coherent were then removed (*N* = 115). The final sample included in the analysis was 8,143 profiles (*M* = 31.97 years, *SD* = 9.82 years).

Of the final sample, 4,107 were male (*M* = 32.61 years, *SD* = 9.69 years), 3,833 were female (*M* = 31.54 years, *SD* = 10.00 years), with the remaining 203 identifying as non-binary (*M* = 27.02, *SD* = 6.88). The majority of profiles identified as heterosexual (81.9%), with the remainder identifying as other sexual orientations. For a more detailed description of the sample, see the supplementary materials.

Pre-processing

All pre-processing of profiles was done in R (R Core Team, 2013) using the tidytext package (Silge & Robinson, 2016) following procedures in Silge and Robinson (2017). Tokens refer to separate unit of meaningful text, in this case separate words. Tokenisation (the process of splitting text into tokens) involved converting all text to lower-case, stripping all punctuation, and separating words into tokens according to spaces. Prior to processing, from the 8,143 profiles, there were 22,610 unique tokens (words) with the average number of words per profile was 69.65 words and an *SD* of 106.83 words. Only single words (unigrams) were considered, as previous work has suggested that including multi-word tokens (e.g., bigrams) often worsens categorisation into known groups (Bekkerman & Allan, 2003). Web links and standalone symbols were removed from the corpus, which is standard when conducting text analysis with online content (Murphy, 2017; Silge & Robinson, 2017). This reduced the corpus to 8,140 profiles and 22,068 tokens.

Proper nouns (names and place names) that were unambiguously proper nouns were removed (for instance, “Grace” is a common female name, but could also be used as a word to meaning elegant or refined, and therefore was not removed, while the name “Mary” does not have an additional meaning, and was therefore removed). Overall, this reduced the corpus to 20,209 unique tokens. Table 1 reports the number of tokens removed for each proper noun category and the source of the proper nouns lists.

Table 1. The number of words removed for each proper noun category and source of the proper nouns list.

Description	Source	List N
Names of People	A list of human names was compiled from the babynames package in R (Wickham, 2017), which includes all names of babies from babynames born in America used more than 5 times.	1,522
Names of Countries	A list of countries were complied from the maps package in R (Becker, Wilks, Brownrigg, Minka, & Deckmyn, 2017).	48
Names of US States	US states included abbreviations (e.g., AK for Alaska). A list of US states were complied from the maps package in R (Becker et al., 2017).	32
Names of Cities and Towns	A combination of stated location collected from the user information, and world cities list from the maps package in R (Becker et al., 2017), which include cities with a population greater than 40,000.	257

Spellchecking was done using the hunspell package in R (Ooms, 2017), which uses the same spell checking algorithms used in much commercial software (e.g., Mac OS X, Google Chrome). Words were spellchecked using US English. Words identified as misspelled were manually checked and corrected. This included common misspellings (e.g., “alot” for “a lot”), expanding common netspeak terms and acronyms (e.g., “lol” becomes “laugh out loud”), and localising text to US English (e.g., “favourite” becomes “favorite"). This reduced the corpus to 20,074 unique words.

Stopwords are common words that do not contribute to a topic and are often removed when doing text analyses. We used the stopword lists provided in the tidytext package in R (Silge & Robinson, 2016), which is developed from a combination of three commonly used lists (onix, SMART, and snowball lists). This reduced the corpus to 18,881 unique tokens. Additional words that were listed in the top 10 occurring words in our corpus of profiles but did not add meaning were also removed. These words were: love, life, people, time, enjoy, person. Often these words were used in distinct context (e.g. “I enjoy X”, “I’m a X person”), and if these words were included, it would lead the LDA to cluster unrelated topics. The remaining top 10 occurring words were judged by the authors to potentially contribute to a specific topic, and were: friends, fun, music, laugh.

After pre-processing, the corpus included a total of 18,875 unique words from 7,973 profiles.

Latent Dirichlet Allocation

The LDA was conducted using the topicmodels package in R (Grün & Hornik, 2011). LDA requires the user to specify the number of topics (k), which in our case was unknown. While increasing k can result in a model that better describes the data, specifying too many topics can lead to overfitting (where the model is specific to the training sample and does not generalise well to other samples). To determine the best number of topics, we used a 5-fold cross-validation method as specified in Blei et al. (2003). This involves dividing the sample into five random subsets and conducting multiple LDAs at varying candidate k's (ranging from 2 to 50 topics), where each training set is made up of four of the subsets and the remaining subset used as a validation set. To evaluate each LDA model we used perplexity, which is a measurement of how well a model predicts the validation set with lower perplexity indicating greater predictive value. The lowest mean perplexity across five runs for each value of k indicated that 25 topics was the most appropriate number of topics (see the supplementary materials for full results).

The LDA is not deterministic, that is, randomness can influence results such that separate runs on the same dataset may give slightly different results. To mitigate this issue, we specified the LDA with 5000 iterations, and an additional burn-in period of 1000 iterations. We ran the LDA 50 times and kept the model with the maximum posterior likelihood. For the full analysis script see the supplementary materials.

The LDA gives two indicators relevant to our interests. First, we receive the logarithimised parameters of the word distribution for each topic (β), which is an indication of how well each word fits in each topic. From the highest occurring words for each topic, we can determine the likely contents of that topic and ascribe a label. This gives insight into the common topics discussed when individuals compose dating profiles.

Second, we receive the posterior topic distribution of each topic for each profile (γ), which could be considered as the probability that a profile includes a given topic. By testing how the topic distributions vary across different demographic groups, we can gain insight into what topics are important to advertise for different individuals. Here, we investigate how the topic probabilities vary according to sex (reported below) and age (reported in the supplementary materials) by running multiple correlations between the demographic statistic and probabilities for each topic, correcting for family-wise error rate using Bonferroni correction (α = .002).

For more information on LDA, see Blei et al. (2003).

Results

Profile Topics

The 25 topics identified by the LDA and the top 10 occurring words for each topic are shown in Figure 1. Labels for each topic were determined by the authors based on the top occurring words for that topic. While some topics were clear, such as displays of personality (e.g., being *honest/caring*, *outgoing/agreeable*, or having a *sense of humour*) or hobbies (e.g., *movies/tv*, *music/art*, or *video games*), other topics were less clear. For example, a topic including the words ‘job’, ‘house’, and ‘car’, was labelled *material stability*, and a topic including judgement words like ‘feel’, ‘real’, ‘perfect’ was labelled *valence*). These unclear topics can be because these topics may represent concepts hard for humans to perceive, or may reflect artificial groupings due to common word uses.

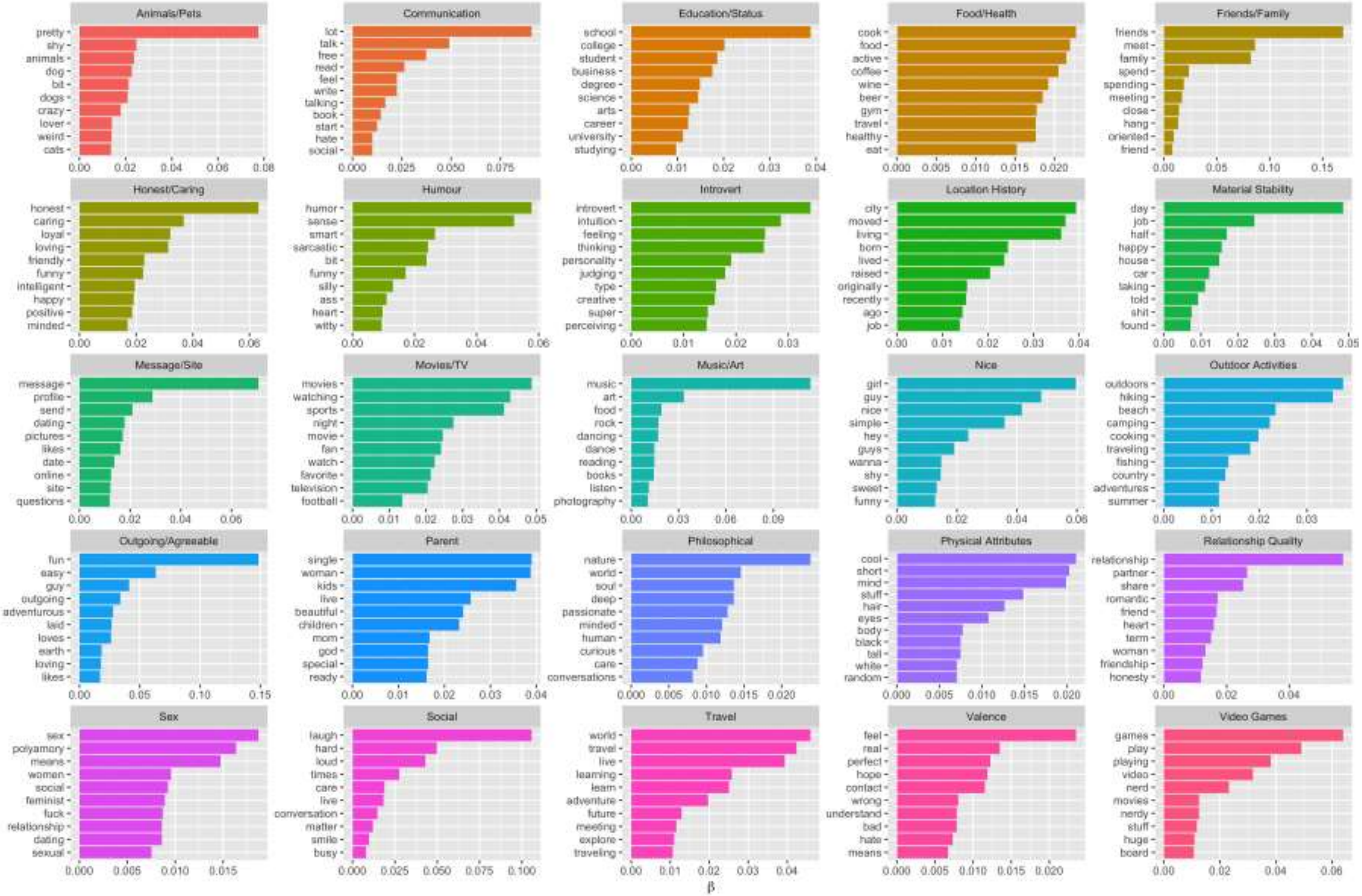
Animals/Pets
pretty
shy
animals
dog
bit
dogs
crazy
lover
weird
cats
0.00 0.02 0.04 0.06 0.08
Communication
lot
talk
free
read
feel
write
talking
book
start
hate
social
0.000 0.025 0.050 0.075
Education/Status
school
college
student
business
degree
science
arts
career
university
studying
0.00 0.01 0.02 0.03 0.04
Food/Health
cook
food
active
coffee
wine
beer
gym
travel
healthy
eat
0.000 0.005 0.010 0.015 0.020
Friends/Family
friends
meet
family
spend
spending
meeting
close
hang
oriented
friend
0.00 0.05 0.10 0.15
Honest/Caring
honest
caring
loyal
loving
friendly
funny
intelligent
happy
positive
minded
0.00 0.02 0.04 0.06
Humour
humor
sense
smart
sarcastic
bit
funny
silly
ass
heart
witty
0.00 0.02 0.04 0.06
Introvert
introvert
intuition
feeling
thinking
personality
judging
type
creative
super
perceiving
0.00 0.01 0.02 0.03
Location History
city
moved
living
born
lived
raised
originally
recently
ago
job
0.00 0.01 0.02 0.03 0.04
Material Stability
day
job
half
happy
house
car
taking
told
shit
found
0.00 0.01 0.02 0.03 0.04 0.05
Message/Site
message
profile
send
dating
pictures
likes
date
online
site
questions
0.00 0.02 0.04 0.06
Movies/TV
movies
watching
sports
night
movie
fan
watch
favorite
television
football
0.00 0.01 0.02 0.03 0.04 0.05
Music/Art
music
art
food
rock
dancing
dance
reading
books
listen
photography
0.00 0.03 0.06 0.09
Nice
girl
guy
nice
simple
hey
guys
wanna
shy
sweet
funny
0.00 0.02 0.04 0.06
Outdoor Activities
outdoors
hiking
beach
camping
cooking
traveling
fishing
country
adventures
summer
0.00 0.01 0.02 0.03
Outgoing/Agreeable
fun
easy
guy
outgoing
adventurous
laid
loves
earth
loving
likes
0.00 0.05 0.10 0.15
Parent
single
woman
kids
live
beautiful
children
mom
god
special
ready
0.00 0.01 0.02 0.03 0.04
Philosophical
nature
world
soul
deep
passionate
minded
human
curious
care
conversations
0.000 0.005 0.010 0.015 0.020
Physical Attributes
cool
short
mind
stuff
hair
eyes
body
black
tall
white
random
0.000 0.005 0.010 0.015 0.020
Relationship Quality
relationship
partner
share
romantic
friend
heart
term
woman
friendship
honesty
0.00 0.02 0.04
Sex
sex
polyamory
means
women
social
feminist
fuck
relationship
dating
sexual
0.000 0.005 0.010 0.015
Social
laugh
hard
loud
times
care
live
conversation
matter
smile
busy
0.000 0.025 0.050 0.075 0.100
Travel
world
travel
live
learning
learn
adventure
future
meeting
explore
traveling
0.00 0.01 0.02 0.03 0.04
Valence
feel
real
perfect
hope
contact
wrong
understand
bad
hate
means
0.000 0.005 0.010 0.015 0.020
Video Games
games
play
playing
video
nerd
movies
nerdy
stuff
huge
board
0.00 0.02 0.04 0.06
β

Figure 1. The 25 topics identified by the LDA and the top 10 words for each topic.

As robustness checks requested as part of the review process, we ran two additional LDAs. First, we excluded profiles that were translated to English through the pre-processing procedure (N = 115). Here, we found that 22 of the 25 topics directly mapped onto topics identified in the original analysis, suggesting that the majority of topics are robust. An additional two topics mapped onto two topics from the original analysis, though did not map on directly ("Health/Food" and "Animals/Pets" becomes "Health" and "Animal/Pets/Food"). Two topics from the original analysis were not represented when translated profiles were excluded from the LDA ("Relationship Quality" and "Nice"), suggesting these topics are perhaps not robust.

Second, we conducted the LDA after stemming words in the corpus. Stemming is the process of reducing words to their root word (e.g., 'stemming' would become 'stem'). Here, 19 topics directly mapped onto topics identified in the original analysis, with an additional four topics being represented though not mapping on directly ("Health/Food" became "Health" and "Food", "Outgoing/Agreeable" became "Outgoing" and "Agreeable", and "Animals/Pets" and "Music/Art" became "Animals/Art" and "Music"). Two topics from the original analysis was not represented in the analysis using the stemmed corpus ("Relationship Quality" and "Social"), again suggesting these topics may not be robust. Full details and results of these robustness checks are reported on pages 14-17 of the supplementary materials.

Topic Distributions and Sex

Given that a profile is more likely to not include a topic than include one, the probabilities that each profile contains each topic were positively skewed; therefore, topic probabilities were log transformed before being used in all subsequent analyses. For each of the following correlations, Bonferonni correction was used to control for multiple comparisons (α = .002). Correlations between topic probabilities and sex for each profile are reported in Figure 2. Men were more likely to discuss education/status, video games, location history, material stability, and food/health in their profiles compared to women, while women were significantly more likely to advertise being honest/caring and animals/pets.

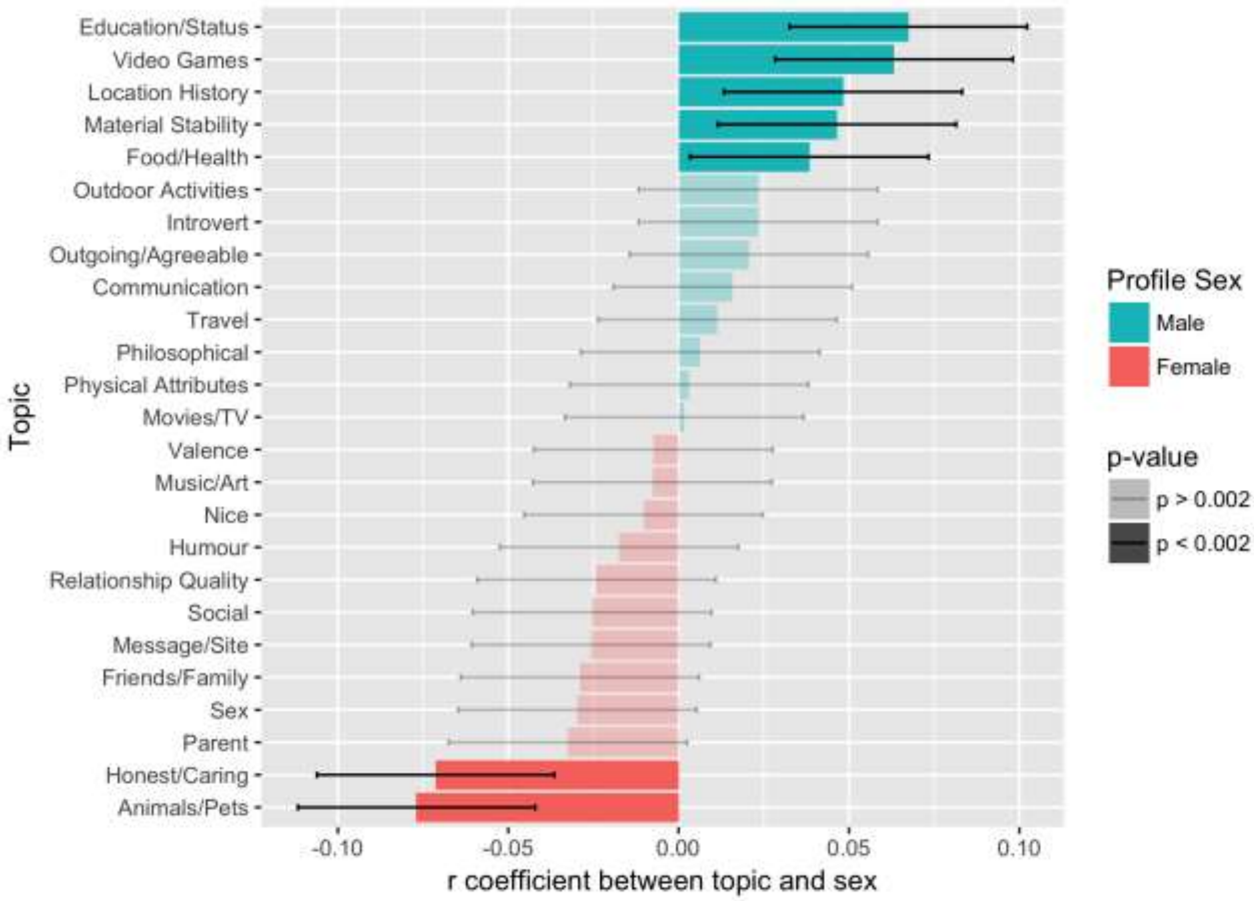

Figure 2. Differences in topic usage between male and female profiles. Error bars represent 99.8% confidence intervals.

Discussion

How individuals present themselves online can give insight into mating-relevant self-concepts. The 25 topics identified by the LDA covered concept across numerous domains, some of which could have been predicted by biological theories of mate choice as advertisements of mate quality (e.g., material stability, physical attributes). Other topics covered personality traits (e.g., Outgoing/Agreeable, Introvert) and interests (e.g., movies/TV, videogames), potentially suggesting that individuals are motivated to describe themselves personably in order to appeal to partners who have compatible personality types or similar interests. While some traits commonly thought to be attractive do not directly map onto a topic (e.g., intelligence), they could potentially be inferred through the topics available (e.g., intelligence, as well as other traits, could be inferred through education/status). This could be because explicitly advertising certain traits could be seen as arrogant, which is negatively associated with attractiveness (Murphy et al., 2015). However, we note that intelligence/creativity was identified as a topic in both robustness checks.

Men were more likely to advertise education/status, as well as material stability; these have previously been theorised to represent resource provisioning potential (Buss & Schmitt, 1993). Men also preferred to discuss location history (often in the context of moving for work or education), video games, and food/health. Women, on the other hand, prefer to advertise being caring/honest, as well as animals/pets (which likely also represent displays of a nurturing nature). These sex differences in topic distributions appear to map well onto biological theories of attractiveness, where women are thought to prefer cues to resource provisioning potential (Buss, 1989; Li et al., 2002), and men are thought to prefer cues to maternal tendencies in women, potentially as an indicated of good parental quality (Law Smith et al., 2012). Our findings suggest that individuals may be aware of these sex differences in mate preferences, and strategically advertise qualities that members of the opposite sex find attractive. Another possibly explanation for these sex differences is that individuals believe that traits that conform to traditional genders are attractive to potential partners, leading men to emphasise traits associated with provisioning, and women to emphasise maternal tendencies.

Some topic distributions where we may have expected a sex difference based on biological theories were not found. For instance, previous work that has indicated physical attractiveness appears to be much more important for women (Buss, 1989; Li et al., 2002); however, we do not find women are more likely to talk about their physical attributes, or highlight being healthy/active or enjoying outdoor activities (both of which could be associated with being physically fit). This lack of finding may be because, in reality, these personal descriptions are accompanied with a profile picture of the user, which would be better suited for displays of physical attractiveness. Similarly, we do not find a significant difference between men and women discussing relationship quality or sex, which could be predicted based on previous work suggesting men show a greater preference for short-term relationships compared to women (Simpson & Gangestad, 1991). Overall, this disassociation between the topics identified and theory could be because individuals have poor insight into what others find attractive, or that theoretical models of mate choice are inappropriate in modern dating context.

STUDY 2

While the topics reported in Study 1 give insight into mating-relevant self-concepts, they cannot provide insight on how the topics are associated with perceptions of attractiveness (i.e., actual preference for these traits). In Study 2, we address this by having a subset of the online personal descriptions collected in Study 1 rated for desirability as a partner by separate participants in the lab. By comparing which topics are associated with overall desirability, we are able to test which topics are potentially universally desirable in a partner. In addition, we can gain insight into how characteristics of the raters influence patterns of desirability. In order to assess whether raters preferred profiles more similar to themselves (as predicted by assortative mating), raters were asked to provide a written description about themselves as if they were writing for an online dating website. We can then apply the LDA clustering algorithm identified in Study 1 to the written descriptions from the raters to determine the probability that the raters mention the same topics. By comparing similarities between topic probabilities written by the raters and those of the profiles being rated, we are able to assess for patterns of individualised mate preferences.

Methods

Participants

One hundred participants were recruited from the University of Glasgow participant pool (49 males, 51 females; *M* = 24.83 years, *SD* = 6.55 years) and participated for either course credit or monetary reimbursement. Ratings were collected in the laboratory. 47 men and 41 women reported being exclusively heterosexual, 3 men and 1 woman reported being exclusively attracted to the same-sex, and 7 women reported being attracted to both sexes equally.

Stimuli

We created four subsets of profiles for rating based on the lab participants' sex and sexual preferences. To ensure variation in topic probabilities, the 10 highest scoring profiles for each topic from each subset category were selected. This resulted in 233 profiles of men who prefer women, 232 profiles of women who prefer men, 174 profiles of men who prefer men, and 91 profiles of women who prefer women (the unequal number of profiles in each subset arose due to the availability of profiles from that category, as well as profiles that were part of the 10 highest scoring profiles for more than one topic). Lab participants who reported preferring both men and women equally rated a combination of male and female profiles that were attracted to their sex. Identifiable information (e.g., usernames, weblinks) was removed from each profile before being presented to participants.

Procedure

Lab participants read and rated 50 profiles randomly selected from the appropriate subset based on their sex and preferences. Participants were instructed to rate the person who wrote the text on desirability as a romantic partner compared to others of their age and sex on a 9-point scale (1 = very undesirable, 9 = very desirable). Profiles were presented in a random order.

Participants were also asked to write a description of themselves as if they were writing a profile that would appear on a dating website. They were instructed that their goal was to write a description that would attract someone they would be interested in, and provide enough detail so that readers can get a good sense of who they are and what they are looking for in a relationship. Participants were provided with an open text field and were not limited in what or how much to write, mimicking online written descriptions in reality. Participants were also asked to provide basic relationship information commonly asked on dating websites, which are not analysed here (e.g., type of relationship seeking for, minimum/maximum age of interest).

Statistical Analysis

Overall desirability. The association between each profile topic and ratings of desirability was estimated using mixed effects modelling. Separate mixed effect models were conducted for each topic, with topic probability for each profile predicting desirability rating. Random effects for rater and profile specified maximally as specified in Barr, Levy, Scheepers, and Tily (2013). Family-wise error rate accounted for via Bonferonni correction. For stability, profiles were only included in the analysis if they received more than 3 ratings from separate participants. Since we could expect that different topics would be desirable in men and women, we report separate analysis for men who rated female profiles and women who rated male profiles here, though the analysis for the combined sample is included in the supplementary materials.

Overall similarity. In order to assess whether similarity between rater and profiles influenced desirability, we first calculated topic probabilities of the rater-written profiles based on the results of the LDA conducted on the online profiles. To do this, written description from the lab participants were first pre-processed using the identical procedure to the web descriptions (described in Study 1). Three participants did not complete the task and an additional participant was removed due to the pre-processing procedure; therefore, data from these participants were removed from subsequent similarity analyses. We then applied the LDA model developed using the web profiles to the profiles collected in the lab. This resulted in estimates of topic probabilities for the 25 topics for each lab participant.

To test if overall similarity in topic probabilities between the rated profile and the profile written by the raters predicts desirability ratings, for each rater-profile interaction, a correlation was run across the 25 corresponding topic probabilities for the rater-profile and the online-profile. To account for the effects of normative desirability (Wood & Furr, 2016), the mean probability across raters and profiles for each topic was subtracted from the probability for each rater/profile before running the correlations. The resulting *r* coefficient was then used as an index of overall similarity, with positive *r*-values indicating greater similarity between rater and profile, while negative *r*-values indicating greater dissimilarity. Overall similarity (as measured by the *r*-coefficients between rater-profile topic probabilities) ranged from -.53 to .88 (M = .01, SD = .21), indicating there was good variability in overall similarity.

Preference for overall similarity was assessed using a linear mixed effect model using the lme4 (Bates, Mächler, Bolker, & Walker, 2015) and lmerTest (Kuznetsova, Brockhoff, & Christensen, 2015) packages in R. Level 1 was specified at the rater-profile interaction level, with desirability rating as the outcome variable, and overall similarity (as indexed by the *r* coefficient described above) as the predictor. Overall similarity was z-standardised at Level 1. To account for non-independence, random effects were specified maximally in accordance with Barr et al. (2013), with lab participant and profile as grouping factors.

Individual topic probabilities. To assess whether similarity in individual topics predicts desirability, for each topic bootstrapping of mixed effect models estimates were conducted. Each bootstrapped model contained the main effects of rater and profile topic probabilities on a given topic, with preference for topic similarity operationalised as the interaction term between the two (i.e., a positive interaction term indicates that preference for a topic increases as their own probability on that topic increases, while a negative interaction term indicates that preference for a topic decreases as their own probability on that topic increases)., Topic probabilities were log-transformed and z-standardised within topic, and outliers were winsorised (+- 3SD). Each mixed effects model was specified maximally with rater and profile used as the grouping variables. Resampling of the similarity estimate being conducted using the lmeresampler package (Loy & Steele, 2016).

Results

The intra-class correlations suggest that 20% (95% CI = .15, .25) of the variance in desirability ratings could be attributed to between-rater factors, while 18% (95% CI = .15, .21) of the variance could be attributed to between-profile factors.

Overall Desirability

Fixed effect estimates between desirability ratings and topic probabilities for male and female profiles are reported in Figure 3 and 4 respectively. For both men and women, outdoor activities, and music/art were significantly positively associated with desirability, while discussing food/health and family/friends was positively associated with desirability in female profiles only. For both men and women, discussing aspects of message/site, sex, and mentioning being a parent was significantly, negatively correlated with desirability.

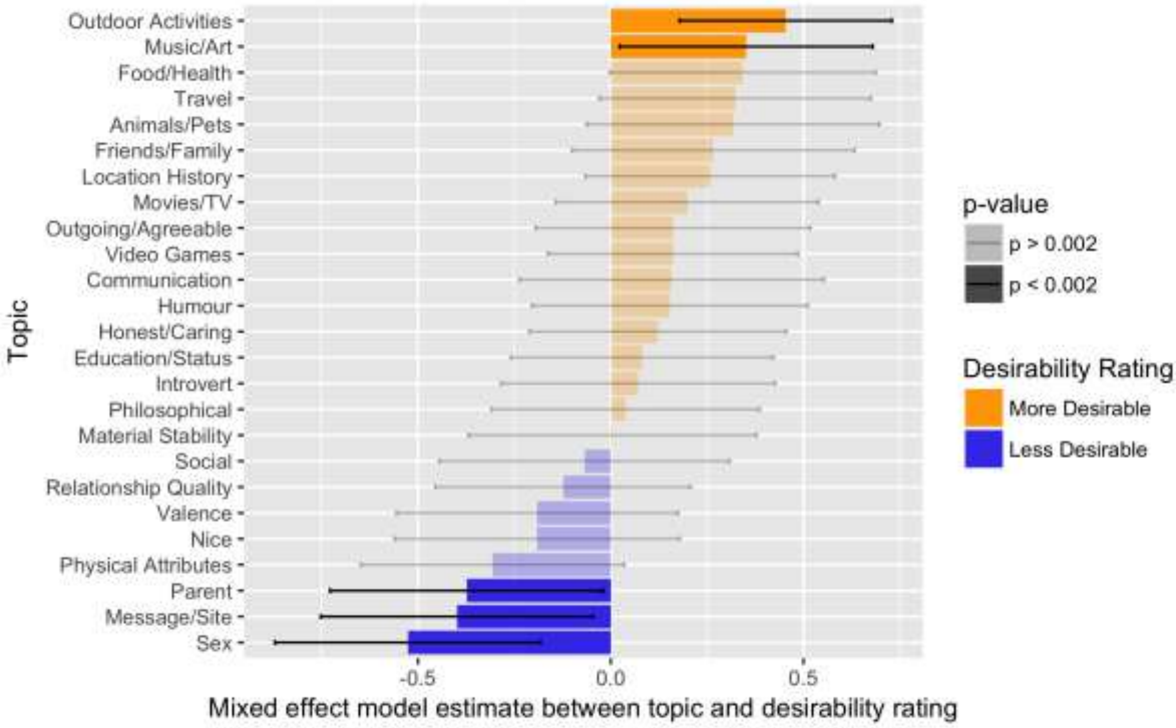

Figure 3. Estimate from the mixed effect model with topic probability predicting desirability ratings for male profiles. Error bars represent 99.8% confidence intervals.

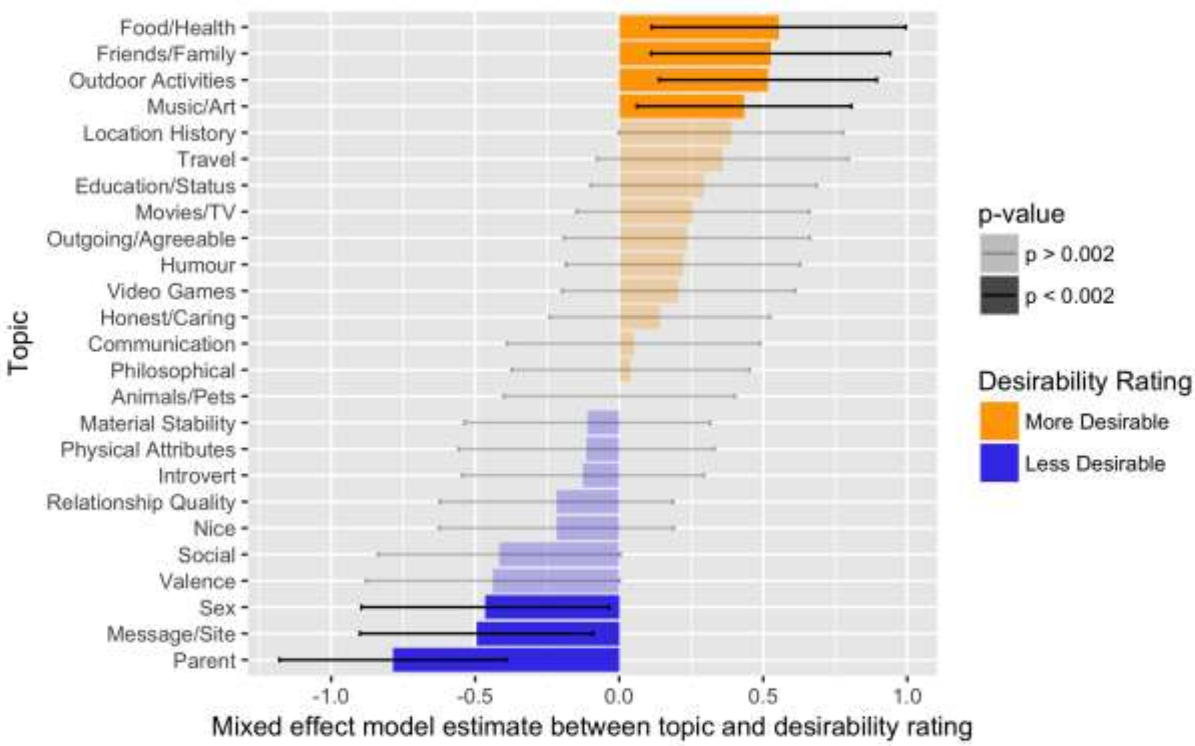

Figure 4. Estimate from the mixed effect model with topic probability predicting desirability ratings and topic probabilities for female profiles. Error bars represent 99.8% confidence intervals.

Similarity

Overall Similarity. The fixed effects from the linear mixed model predicting desirability ratings are reported in Table 2 and shown in Figure 5. There was a significant, positive effect of similarity, suggesting that raters considered profiles more desirable when the profile was more similar to their own. For full model specification and results (including random effects estimates), see the supplementary materials.

Table 2. Fixed effects for the linear mixed effect model with overall similarity predicting desirability rating.

	Estimate (Std. Error)	*t* statistic (approx. *df*)	*p*-value
Intercept	4.53 (.11)	40.98 (119.67)	< .001***
r similarity coefficient	.21 (.03)	6.10 (90.20)	<.001***

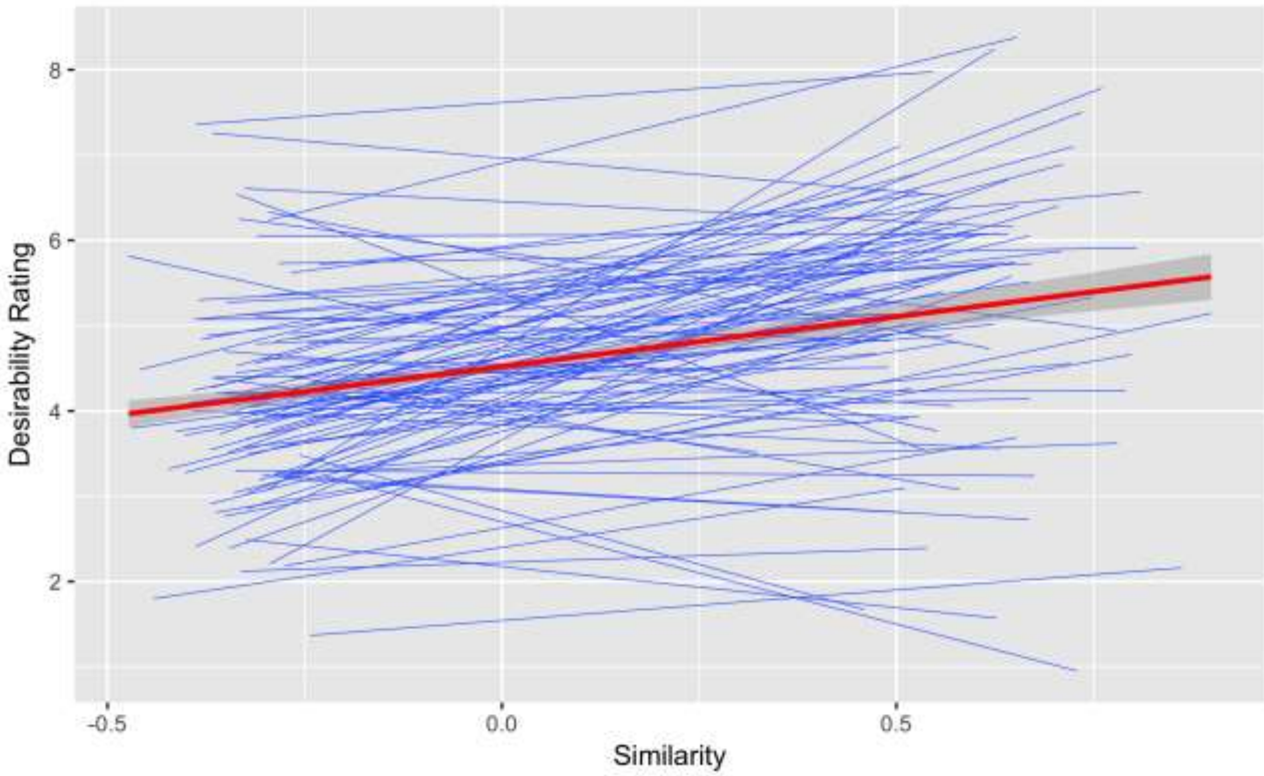

Figure 5. Association between overall similarity between rater and profile and desirability ratings. The red line indicates the relationship across the whole sample, while the blue lines indicate the relationship for each rater.

Topic Similarity. We also tested whether similarity on individual topic probabilities between rater and profile predicted desirability ratings. Results from the bootstrapped samples revealed that preference for similarity was consistently different from zero for two topics across the 100 resamples (see Figure 6). These were topics describing the writer as *nice* as well as being *outgoing/agreeable*. While preference for most of the other topics trended positively, we are unable to confidently conclude that similarity on those topics predict desirability ratings. Only a handful of topics suggested a possible preference for dissimilarity (e.g., *humour*), but again, we are unable to conclude this confidently based on the bootstrapped samples.

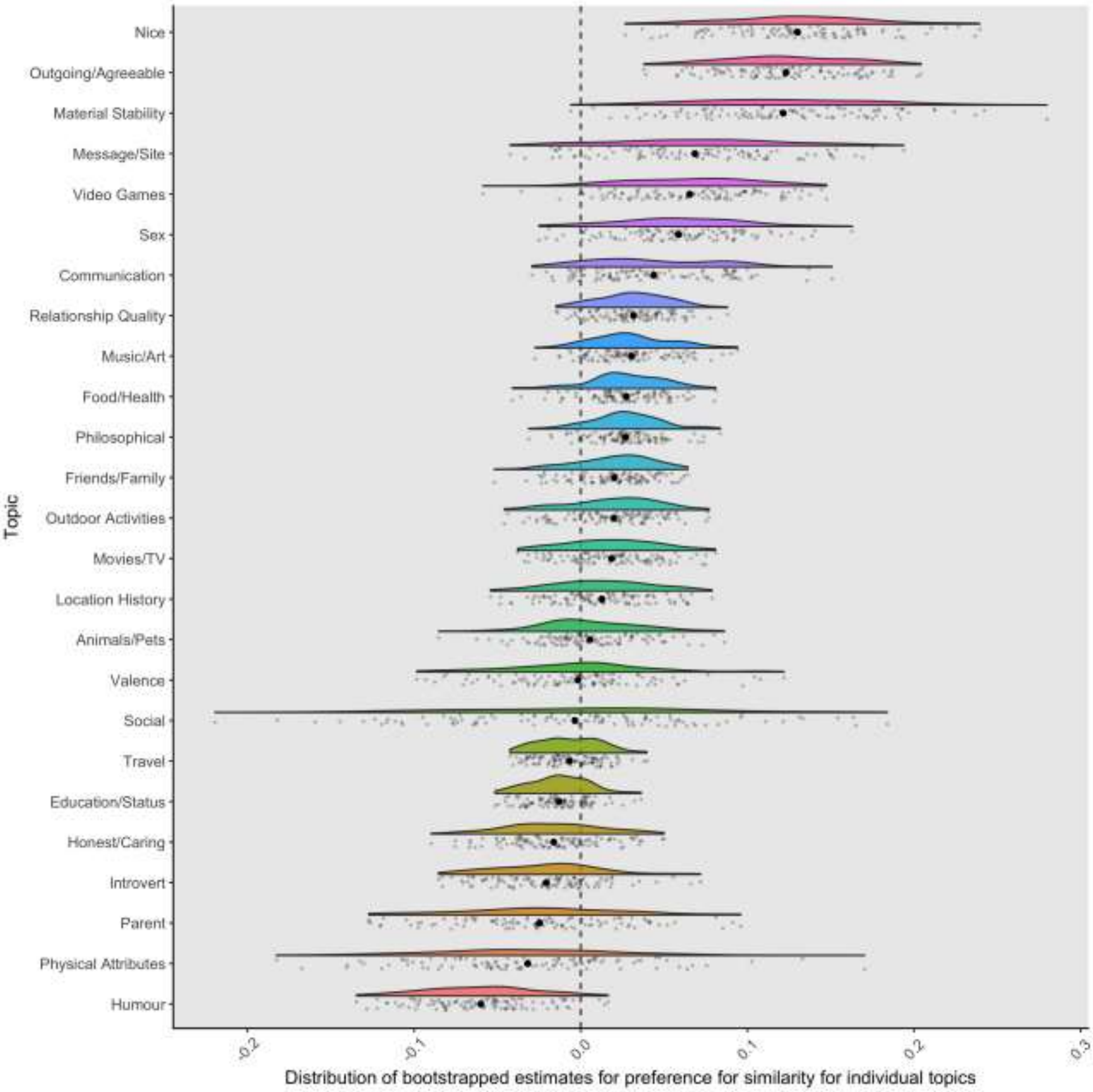

Figure 6. Distributions of bootstrapped estimates with 100 repetitions per topic for the linear mixed effect models of individual topic similarity predicting desirability ratings. Larger solid points represent the mean estimate for that topic across the 100 resamples.

Discussion

For both male and female profiles, there was a significant preference for those that discussed outdoors activities, while discussing food and health was significantly positively associated with desirability in female profiles (this relationship was trending, but non-significant in male profiles). One possible explanation is that, given that the written descriptions were presented without images, raters could be using topics such as outdoor activities and food/health to estimate the physical attractiveness of profile writer, as individuals who are more likely to discuss being healthy and enjoying outdoor activities are also more likely to be physically fit. This interpretation is consistent with previous studies that have found that physical attractiveness it considered one of the most important traits when assessing a potential partner (Fiore, Taylor, Mendelsohn, & Hearst, 2008; Lee, Dubbs, von Hippel, Brooks, & Zietsch, 2014; Walster, Aronson, Abrahams, & Rottman, 1966). Our findings extend this by suggesting that even in the absence of visual cues, estimates of physical attractiveness based on non-visual cues appear to still influence mating decisions.

Discussing music and art was positively associated with desirability in both male and female profiles. Some theories suggest that musical and artistic ability are an honest signal of underlying genetic quality (Miller, 2000), for instance, an individual’s intelligence (Mosing et al., 2015). However, studies investigating this have typically emphasised that displays of musical and/or artistic ability should only be advantageous for men (e.g. Madison, Holmquist, & Vestin, 2017; Watkins, 2017). Our findings suggest that displays of musical/artistic ability are also important for female attractiveness. This finding is perhaps unsurprising given that human mating involves mutual mate choice, while previous studies investigating the role of musical/artistic ability are often inappropriately derived hypotheses from animal models of mate choice where males compete for choosy females (Stewart-Williams & Thomas, 2013). Given that music/art was consistently found with both male and female profiles along side topics that may indicate physical attractiveness (a well investigated trait in mate preference research), these findings suggest that the role of music and/or art in human mating may warrant further investigation.

We found that both male and female profiles that were more likely to discuss sex were overall found less desirable. This is consistent with previous findings that have found that men, compared to women, show a greater preference for short-term, uncommitted relationships and are more likely to seek extra-pair mates (Barta & Kiene, 2005; Schmitt, 2005), and also findings that men value chastity in a partner (Buss, 1989). Similarly, our finding that profiles who discuss being a parent were rated as less desirable is consistent with previous work that has indicated that potential mates who have already had children less attractive. This is thought to be because individuals who already have children would have fewer resources (e.g., time, energy, or physical resources) to invest in potential future offspring (Stewart, Manning, & Smock, 2004).

For both male and female profiles, we found a negative association between desirability and profiles that discussed aspects of the dating website platform (e.g., referring to the profile picture or inviting the reader to send them a message). One possibility is that users who are actively inviting messages from other users are seen as over-eager, which has previously been found to be undesirable (Latty-Mann & Davis, 1996). Another possibility is that this negative association could also be an artefact of the descriptions being presented to raters in the absence of these elements (e.g., referring to a profile image that is unavailable to the raters), and therefore judged more harshly.

Interestingly, traits more likely to be advertised by men or women (as identified in Study 1) were not associated with desirability ratings. This suggests there is a potential disconnect between the mating-relevant self-concept differences held by each sex and what is actually rated as attractive. This is consistent with previous findings that show that, generally, individuals are poor at discerning mating relevant traits, including their own preferences (Eastwick, Eagly, Finkel, & Johnson, 2011). Our results could suggest that individuals have poor insight into what is actually attractive. Instead, individuals are discussing other characteristics, potentially based on other pre-conceived notions (indeed, sex differences in characteristics advertised are in line with traditional sex roles; Eastwick et al., 2006). Another possibility is that the disconnect is an artefact of recruiting raters from a university participant pool, the majority of which were young, educated, students living in a Western city, while the profiles collected online were drawn from a global population (ethical considerations prevented recruitment of raters online). As such, we could expect that if the raters were more representative of the sample of profiles, we could find more alignment between traits being advertised and those associated with desirability ratings. Also, if written descriptions were presented to raters with visual information (i.e., profile pictures), other topics that are not potential indicators of physical attractiveness (such as those to do with status/resource provisioning or displays of a nurturing nature) may become more important when assessing profile desirability.

There was a significant effect of overall similarity on desirability ratings, supporting previous findings of assortative mating (e.g. Hitsch et al., 2010). However, we are only able to confidently conclude that similarity on the *nice* (which contains words such as ‘nice’, ‘simple’, and ‘shy’) and *outgoing/agreeable* topics were associated with desirability ratings. Both topics appear to capture agreeableness and/or introversion/extraversion, perhaps suggesting raters show assortative mate preference for these personality traits. Note that our findings do not to suggest that our finding that overall similarity predicted desirability ratings is solely driven by these two topics; indeed, there was a positive trend towards preference for similarity for a good proportion of the remaining topics. Given that this data is inherently noisy, we could expect that effects of similarity would be small; therefore, we may lack the necessary power to detect a significant effect for the other topics. As such, a lack of a significant effect should not be interpreted as evidence for no similarity effect for any individual topic. We also note that using a correlation in topic probabilities as a measure of similarity is limited as it focuses on similarity in patterns, rather than absolute similarity. This could be addressed by calculating similarity using a different method, such as Euclidean distance (see Conroy-Beam & Buss, 2017).

Across both similarity analyses, we found considerable variability in preference for similarity. The overall similarity analysis indicates variance between individuals for preference for similarity (random effects indicate that 15.55% of between-individual variability could be explained by individual difference in preference for similarity; this is also visualised as by the variability in slopes in Figure 6). This finding perhaps indicating that there are individual differences to the degree that individuals prefers a partner similar to themselves. Similarly, variability also existed in preference for similarity across different topics; for instance, topics such as “social” show a wide range of both preference for similarity and dissimilarity compared to other topics. Understanding this variation in similarity preference is not well understood, and could be an avenue for future research.

GENERAL DISCUSSION

Overall, while some of our findings are explained well by current theoretical models (e.g., that men advertise cues to resource provisioning potential, while women advertise cues to nurturing qualities), other findings are harder to explain (e.g., that these traits were not associated with desirability). One explanation for the disconnect between our findings and previous theoretical models is that these specific attributes identified by previous theories may only show a significant effect when those attributes are isolated, as is the norm in tightly-controlled experimental designs. However, in reality, due to the massive multivariate nature of human mate preferences, these traits may only play a minor role in informing human mate choice. In fact, given that theory-driven research can be susceptible to researcher bias (Jack et al., 2018), if the traits advertised by men and women reflect pre-conceived biases on what is attractive (for instance, because they are based on traditional sex roles), then these same biases could have influenced current theoretical models.

A limitation of the studies presented here is that the LDA is unable to distinguish between qualities the writer is advertising vs. the qualities the writer desires in a partner. Given that written descriptions specifically asked for information about the writer, the majority of descriptions were advertising qualities of the writer. Indeed, in a random subsample of 1000 profiles from Study 1, only 7.60% of the total word count was dedicated to discussing qualities desired in a partner. Regardless, future research could distinguish between the two and conduct separate LDAs to gain insight into both what traits individuals advertise, but also traits that individuals request in a partner.

Also, our analyses are based purely on written text. A large proportion of mate preference research focuses on physical attributes, and indeed, in reality these texts would be presented with images of the profile writer. Little is known about how physical cues are integrated with non-physical cues when informing mate choice decisions. One possibility is that individuals first use physical attractiveness as an indicator of whether to consider a potential partner, and only once a potential mate meets this criterion are other traits used to assess compatibility (i.e., a threshold model of mate choice). This is consistent with our finding that raters in Study 2 first prioritise topics associated with physical attractiveness. Future research could focus on how information from written text is used to inform mate choice decisions when accompanied with visual information from a picture.

While we aimed to collect online profiles that represented the global population, the majority of these users were young adults residing in Western countries, and predominately from the US. This population is typical of those that uses online dating, but results may not generalise well to other populations, such as those in non-Western countries, older individuals, or those who do not have access to the Internet. Other considerations include individual differences between the type of person who is likely to use online dating and those who prefer conventional dating. For instance, previous work has shown that individuals with low dating anxiety are more likely to use online dating than those with high dating anxiety (Valkenburg & Peter, 2007).

Our study provides findings that warrant further investigation to identify whether and how they should be incorporated into current theories of human mating. For instance, a potential avenue for future research is whether individuals have accurate mating relevant self-concepts, given the discrepancy between topics advertised and those preferred. Another is the role that music/art play in human mating. Overall, our data-driven analyses suggest that both universal and individualised preferences are important when making mate choice decisions.

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Open Data Statement

We are unable to share the data from this project because it was part of getting ethical approval. This is for two main reasons: first, even though profiles were already publicly available, we did not collect explicit consent from the profile writers. Therefore, we cannot reproduce their content and make it available in contexts they did not intend. Second, data cannot be shared in order to protect the anonymity of the profile writers. However, we note that we provide the full analysis code for the project, which is available at osf.io/vj3d5.

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